Potential Application of Using Smartphone Sensor for Estimating Air Temperature: Experimental Study

Kun Song, Xichuan Liu, and Taichang Gao

***Abstract*—High temporal–spatial resolution measurement of the air temperature is important for human health and research on the urban heat island. Since conventional methods can hardly meet the demands, a novel measurement of the air temperature has been proposed by using the battery temperature sensor of the smartphone, which can provide a refined data in a crowdsourcing way. First, a heat transfer retrieval model among the air temperature, battery temperature, and the pocket of the clothing or the desk is established. Then, coefficients of the retrieval model are obtained by the data set measured through the smartphone and the thermometer in the linear fitting method. Finally, we retrieve the air temperature in a specific site with a time resolution of 1 min based on the retrieval model by three independent smartphones. The retrieval air temperature of four models strongly correlates to the true value, indicating that the retrieval model can sense the variation of the air temperature. Meanwhile, root-mean-square errors of the 1st and 4th model are 0.35 °C and 0.45 °C, implying the high retrieval accuracy. The results suggest that the retrieval model can provide a short timescale (minute) and robust estimation of the air temperature by smartphone temperature sensors.**

***Index Terms*—Atmospheric sounding, crowdsourcing, measurements of air temperature, smartphone battery sensor.**

I. Introduction

TEMPERATURE is a very important meteorological factor [1]. It is closely related to human life. Heat wave may negatively influence human health and increase the mortality rates [2]–[4]. Between 4 and 18 August 2003, average daily temperatures across France exceeded 35 °C, and the unprecedented temperature resulted in an overall 60% increase in mortality compared with the seasonal norm for the entire country [2]. Moreover, many studies, researching the urban heat island (UHI), indicate that future heat stress is amplified in urban areas [5], [6]. UHI is the difference in canopy air temperature between the rural background and the urban core. Therefore, it is of significance for the higher temporal–spatial resolution measurements of urban atmospheric temperature [7] with ongoing and projected global urbanization [8]. However, traditional measurement of the air temperature in urban areas only covers a small area for intensive measurement [9], [10], which leads to be lack of necessary measurements in other areas. As a result, it can hardly meet the demands of high temporal–spatial measurement in reality. It is essential to develop a method to solve the problem.

Besides professional measurements of the air temperature, citizens as data providers show the potentials in recent years, especially in urban areas [5], [11]–[13], which can provide data of the higher spatial resolution in a cost-efficient way. For example, the Netatmo company develops the weather station for interested citizens to observe the atmospheric condition indoor and outdoor (https://www.netatmo.com/product) and thus, a chance is given to collect the atmospheric data (including the air temperature) around the world by the Netatmo server [7], [14], [15]. Meanwhile, the concept of crowdsourcing, defined by Dickinson *et al.* [16] as "getting an undefined public to do work, usually directed by designated individuals or professionals," is a new approach to acquire huge amounts of data to explore the other application. Inspired by this concept, there are some research on rainfall estimation, which is retrieved by microwave rain-induced attenuation measured through smartphone signal [17]. Sensor-laden wearable systems also have the potential of estimating the temperature, such as the printed chipless antenna and the smart bandage with temperature sensors by means of change in resistance [18], [19]. Additionally, an innovative method was proposed by Overeem *et al.* [20] for measuring the air temperature in urban by smartphone battery sensors in recent years. It is a development of a scaling mechanism allowing real-time conversion of battery temperature to air temperature. Overeem *et al.* have taken advantage of 6-month data sets of the battery temperature measured by smartphone temperature sensors from eight cities, with on 844 selected battery temperature readings per city per day. Then, a transfer heat model between smartphone, user body, and air temperature is employed to retrieve a daily averaged, city-averaged air temperature. Then, based on the study of Overeem *et al.*, Droste *et al.* [21] researched a much longer and denser data set of OpenSignal for São Paulo to retrieve the air temperature in Brazil. They explore the potential of the heat transfer model at refined spatial and temporal scales.

The crowdsourcing method for measuring the air temperature by smartphones is promising, as smartphones are widely spread in the world. Almost all smartphones have built-in battery temperature sensors that monitors the temperature of the battery in order to prevent damage when the battery is

Manuscript received 18 October 2020; revised 29 December 2020 and 8 February 2021; accepted 28 February 2021. Date of publication 3 March 2021; date of current version 8 August 2022. This work was supported by the National Natural Science Foundation of China under Grant 41975030, Grant 41505135, and Grant 41475020. *(Corresponding author: Xichuan Liu.)*

The authors are with the College of Meteorology and Oceanography, National University of Defense Technology, Changsha 410005, China (e-mail: songkun_0521@foxmail.com; liuxc2012@hotmail.com; 2009gaotc@gmail.com).

Digital Object Identifier 10.1109/JIOT.2021.3063488

too hot [22], which can provide the high temporal–spatial resolution measurements for the protection of human health and the research on UHI. In this article, we explore the potential of the air temperature measurement by the smartphone battery sensor. First, a heat transfer model between the air temperature, battery temperature, and the pocket of the clothing or the desk is established, which is similar to Overeem *et al.* Different from retrieving the daily averaged, city-averaged air temperature by many smartphones of Overeem *et al.*, we retrieve the air temperature in a small scale and specific site with a time resolution of 1 min based on the heat transfer model by three smartphones, which is more feasible in reality. In addition, the coefficients of the estimation model in [20] and [21] are assumed to be constant. However, coefficients for each smartphone in different periods are different due to the variation of the thermal conductivity. Therefore, coefficients of the estimation model in our study are different for different smartphones and periods. The coefficients of the retrieval model are calculated by the data set measured by the smartphone and the thermometer datalogger in the linear fitting method. Note that the temperature data, available through some weather apps on the phone, is measured by some organizations such as weather stations, but they need the Internet connection when the temperature data is accessible. However, the application of the estimation of the temperature data by the phone battery sensors can access the temperature data in anytime and anywhere even without Internet connection. Meanwhile, we develop a lightweight app to obtain the smartphone battery temperature, which is easy to embed itself in other common apps in the future. This study may provide huge amount of data for meteorological departments and give more refined air temperature with high temporal and spatial resolution in a crowdsourcing way in the future. Additionally, the air temperature variations could be influences on the water temperature and the variations of dissolved oxygen. A big influence of water temperature on water acidification [23]. Based on the mapping air temperature by smartphone battery temperature sensors, the water temperature also can be estimated by using the model between the air temperature and the water temperature such as air2stream model [24], which is helpful for water pollution monitoring.

In this study, we propose a method of estimating the air temperature by the battery temperature sensor of the smartphone. The method can provide real-time air temperature measurement with the 1-min resolution, which is much higher than the traditional methods. Meanwhile, the novel method has the potential of providing high spatial air temperature measurements by collecting the huge amount of data of the billions of widespread smartphones via the Internet. This article is organized as follows. Section II introduces the data measured by the smartphone battery temperature between March 19, 2019 and April 19, 2019 and the air temperature retrieval model based on the smartphone battery temperature. Section III describes the retrieval result using the data set measured by three smartphones in order to verify the retrieval model. Section IV discusses some issues and Section V concludes this article.

II. Material and Methods

A. Air Temperature Retrieval Model

The air temperature retrieval model of the study is based on the heat transfer model proposed in [20]. Suppose that a smartphone is put on a desk or carried in a pocket of user's clothing in a room. Let E_c (W) represent the thermal energy generated by the smartphone per unit time. Almost all of E_c will be turned into heat by conductive heat flow, then convection and radiation can be neglected. Thus, E_c is balanced by heat outflow to the air (E_a (W)) and to the desk or the pocket (E_o (W)). E_a or E_o between two adjacent systems is proportional to the difference of the temperature between two systems. We further assume that there are no other heat sources. As a result, the equation among E_c, E_a, and E_o may be written as follows, assuming stationarity:

$$\begin{cases} E_c = E_a + E_o \\ E_a = k_a(T_c - T_a) \\ E_o = k_o(T_c - T_o) \end{cases} \tag{1}$$

where T_c(°C) is the smartphone battery temperature measured by the smartphone battery temperature sensor, T_a (°C) is the true air temperature, and T_o (°C) is the external object temperature, such as desk or the user's body, which can be assumed to be constant approximatively in a period. k_a (W/°C) and k_o (W/°C) represent coefficients of heat conduction between two adjacent systems, respectively. Equation (1) then can be rewritten as follows:

$$T_a = \left(1 + \frac{k_o}{k_a}\right)T_c - \left(\frac{k_o}{k_a}T_o + \frac{E_c}{k_a}\right). \tag{2}$$

It is further assumed that E_c, k_a, and k_o are constant for each sampling time (1 s in this article). Then, a formula can be obtained as follows:

$$T_{a,i} = k_i \cdot T_{c,i} + b_i \tag{3}$$

where subscript i represents the ith measurement of the smartphone battery temperature. A time-average method is adopted in the time interval of N for getting a more robust estimate of T_a

$$\frac{1}{N}\sum_{i=1}^{N} T_{a,i} = \frac{1}{N}\sum_{i=1}^{N} k_i \cdot T_{c,i} + \frac{1}{N}\sum_{i=1}^{N} b_i \tag{4}$$

where k_i and b_i are assumed as to be constant approximatively in the same phone and same site. Equation (4) can be rewritten as

$$\overline{T}_{a,j} = k \cdot \overline{T}_{c,j} + b \tag{5}$$

where $\overline{T}_{a,j}$ and $\overline{T}_{c,j}$ are the average air temperature and the smartphone battery temperature of the jth time interval measured by the smartphone battery sensors, and k and b are constants. The value of k represents the sensitivity to the variation of the air temperature. If $k = 1$, then $\overline{T}_{c,j}$ would change 1 °C when $\overline{T}_{a,j}$ change 1 °C. Equation (5) is adopted as the air temperature retrieval model, meanwhile, $\overline{T}_{a,j}$ and $\overline{T}_{c,j}$ are linear, approximatively.

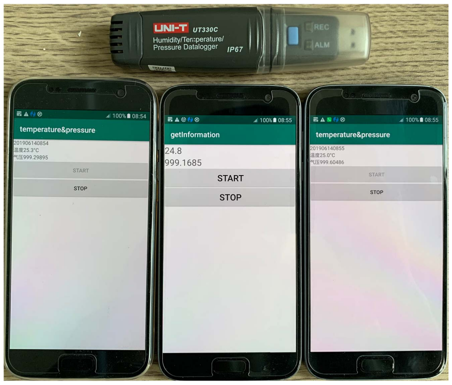

Fig. 1. Three cellphones, the thermometer, and the application in the study.

B. Data of the Smartphone Battery Temperature

The smartphone model in this study is Samsung G9300 and the system of the phone is Android 6.0. The smartphone has a battery temperature sensor which is applied for monitoring the real-time battery temperature and protecting the phone from high temperature. Meanwhile, an Android application has been developed in order to record the real-time data measured by the smartphone battery temperature sensor with the sampling time of 1 s. And the measurement resolution of the smartphone battery sensor is 0.1 °C. In addition, to verify the air temperature retrieval model presented in the study, we have also measured the air temperature by the thermistor thermometer of the UT330C datalogger. Sampling time of the datalogger is 1 min, the resolution is also 0.1 °C, and the measurement accuracy is ±0.5 °C.

Three smartphones and one UT330C datalogger are put in the same room, located in the College of Meteorology and Oceanography, National University of Defense Technology, Nanjing, China. In order to improve the representativeness of the smartphone, three smartphones are put in different position in a room: the first smartphone is put on the desk, the second one is put on the sofa, and the third one is put into the pocket of the down jacket. Simultaneously, the thermometer is put on the central of the room to measure the air temperature of the room. Note that the windows of the room are always opened for keeping up with the variation of the outdoor temperature. Fig. 1 shows the smartphones, the UT330C datalogger and the application for recording real-time smartphone battery temperature.

The values of the smartphone battery temperature are calculated by a method of 1-min average, which can be compared with the UT330C datalogger. Fig. 2(a) gives the comparison between the smartphone battery temperature measured by the smartphone sensors and the true air temperature measured by the UT330C datalogger from March 19, 2019 to April 19, 2019. Additionally, the average battery temperature of three smartphones is also shown in the figure. It shows that the smartphone battery temperature strongly, positively correlates with the true air temperature, indicating that the smartphone battery sensors can sense the variation of the air temperature. Fig. 2(b) gives correlation coefficients (ρ^2) between the battery temperature of three smartphones and the air temperature measured by the UT330C datalogger of each single day. It further indicates that the battery temperature of all three smartphones correlates with the true air temperature strongly in most of the time, especially for the first smartphones whose ρ^2 is around close to 0.9.

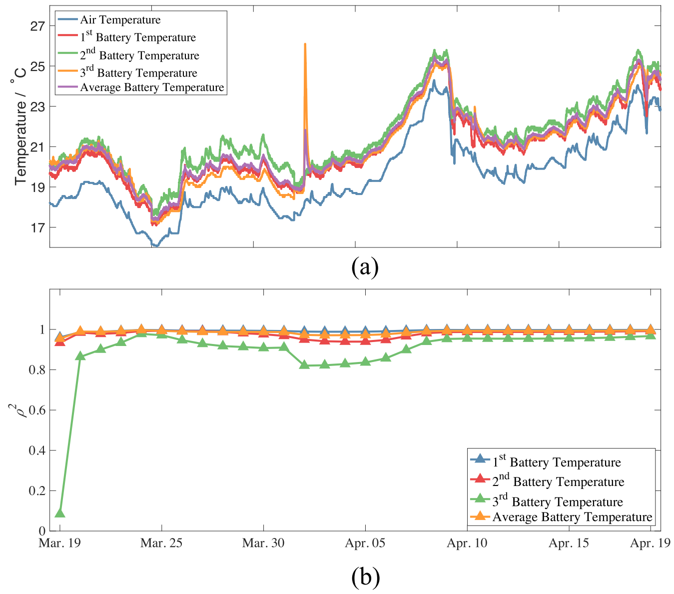

Fig. 2. Measurements of the air temperature and the battery temperature of cellphones. (a) Time series of the battery temperature measured by three cellphones and the air temperature measured by UT330C. (b) Correlation coefficients ($\rho 2$) of different dates between the battery temperature of three cellphones and the air temperature. Note that the average battery temperature is calculated by the average of battery temperature of three cellphones.

However, ρ^2 of the third smartphone is lower than the other two because it is put into the pocket of the down jacket, which is less sensitive to the variation of the true air temperature. Moreover, ρ^2 between the average battery temperature of three smartphones and the air temperature is also given in the figure. The result shows correlation is getting higher clearly using the average battery temperature compared with the second and third smartphones, indicating that the average method can smooth or even eliminate the outlier (e.g., the data on March 19, 2019 and April 12, 2019 of the third smartphone). Therefore, it may be feasible to retrieve the air temperature using the average battery temperature of several smartphones based on the retrieval model.

III. Results

A. Fitting Results of k and b

Estimations of the values of k and b are necessary to retrieve the air temperature using the retrieval air temperature model. In this study, we approximately assume that $\overline{T}_{a,j}$ and $\overline{T}_{c,j}$ are linear. Therefore, the linear fitting method is adopted to calculate the values of k and b. Fig. 3 shows the fitting results between the battery temperature of three smartphones and the true air temperature measured by the UT330C datalogger on different dates. Also, the fitting results between the average battery temperature and the true air temperature are shown in the figure. It can be seen that the fitting results of the first smartphone and the average keep stable in different dates and values of k are both close to 1, while results of the third smartphone are variational.

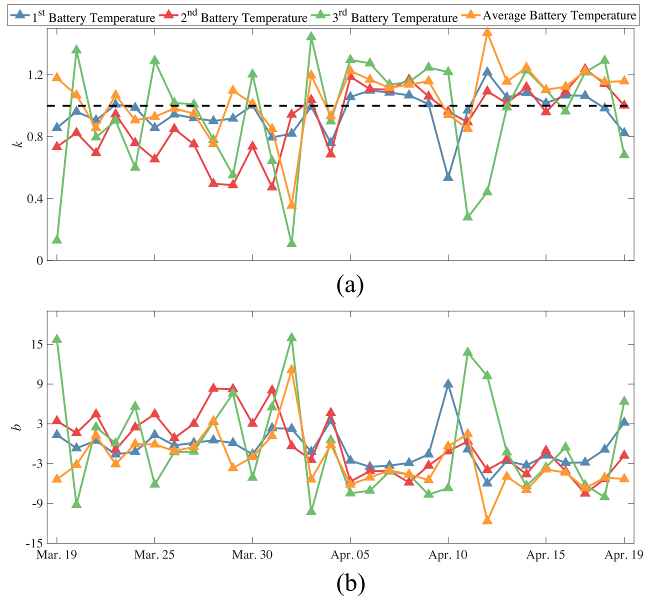

Fig. 3. Fitting results of the retrieval air temperature model. (a) Values of retrieval air temperature model of k for each day. The black dashed line represents that k = 1. (b) Values of retrieval air temperature model of b for each day.

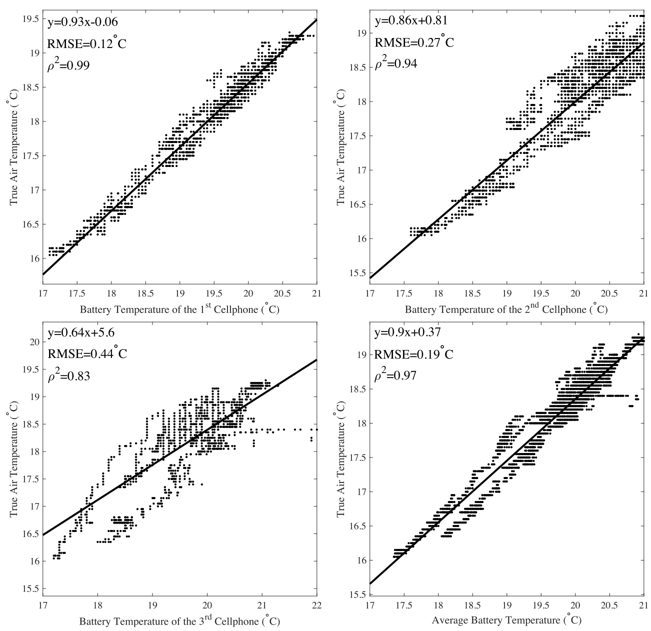

Fig. 4. Fitting values of k and b of the retrieval model calculated by the training sets of four groups. Date of the training set are from March 19, 2019 to April 4, 2019 (21 600 min).

B. Retrieve Air Temperature Using the Smartphone Battery Temperature

In this section, we have four data sets of the battery temperature measured by smartphone sensors: the first smartphone, the second smartphone, the third smartphone, and the average temperature of three smartphones. As for each set, the data set is divided equally into two parts: 1) training set and 2) test set. The training set is used to calculate the values of k and b of the retrieval air temperature model by the linear fitting method and the test set is used to validate the accuracy of fitting values of k and b of the retrieval model.

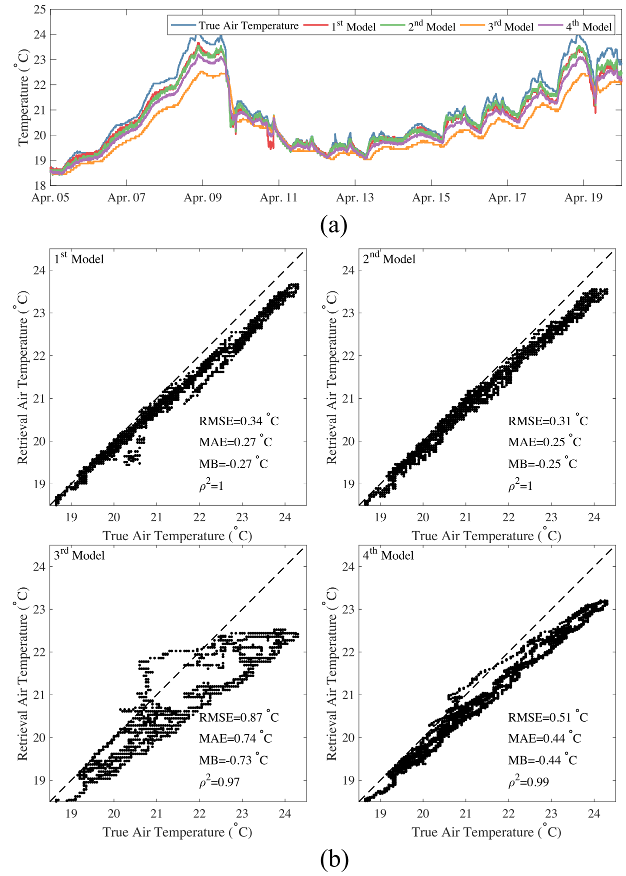

Fig. 5. Retrieval results by four models. (a) Time series of the retrieval air temperature of test set and the true air temperature. (b) Test results of the retrieval models. MAE: mean absolute error, and MB: mean bias.

The values of k and b of four groups are fitted by training sets and given in Fig. 4. The value of k is close to 0.9 except the third smartphone ($k = 0.64$) because it is put into the pocket of the clothing and less sensitive to the variation of the temperature. Meanwhile, root-mean-square errors (RMSE) between the true air temperature and the value retrieved by the fitting model of four groups are calculated for evaluating the model. RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{M}\left(T_{r,i} - T_{t,i}\right)^2}{M}} \tag{6}$$

where $T_{r,i}$ is the retrieval temperature by models, $T_{t,i}$ is the true temperature by the UT330C datalogger, and M is the number of $T_{r,i}$. RMSEs are between 0.12 °C and 0.44 °C, which indicates that the fitting model is close to the true value. Note that we use "the first to fourth model" to represent the fitting equation based on (5) of four training sets for the convenience of the following illustration in the study.

Fig. 5(a) shows the retrieval air temperature ($\overline{T}_r$) of the test set using four retrieval models. In general, $\overline{T}_r$ of four models strongly positively correlates with true air temperature ($\overline{T}_a$). Furthermore, $\overline{T}_r$ of the first model and the fourth model is closer to $\overline{T}_a$, compared with the second and the third model. Additionally, a more complete overview by scatter

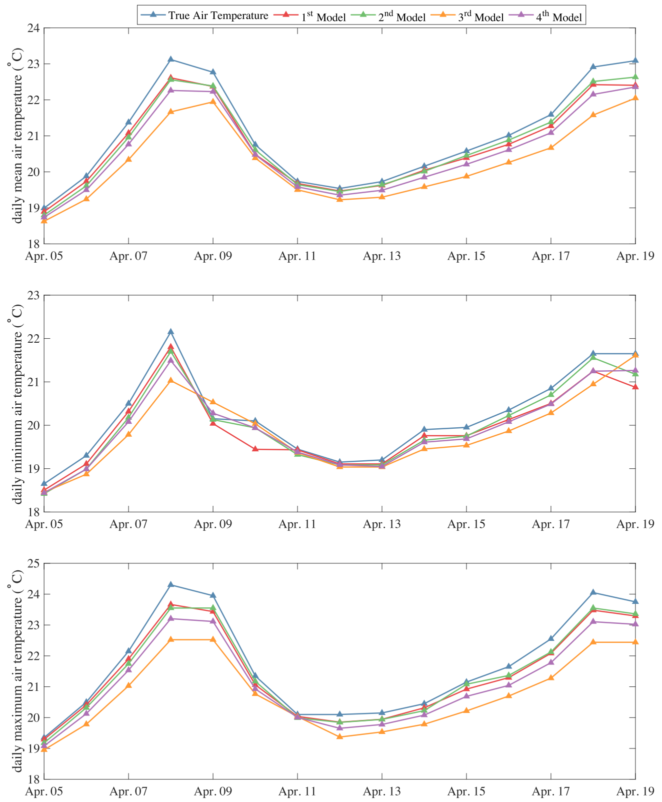

Fig. 6. Retrieval results for daily mean, minimum, and maximum air temperature by four models.

plots between $\overline{T}_a$ and $\overline{T}_r$ are given in Fig. 5(b). RMSE, mean absolute error (MAE), and mean bias (MB) are calculated. MAE and MB reflect the bias between the retrieval and the true value. MAE and MB are calculated as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{M} \left| T_{r,i} - T_{t,i} \right|}{M} \tag{7}$$

$$\mathrm{MB} = \frac{\sum_{i=1}^{M} \left(T_{r,i} - T_{t,i} \right)}{M} \tag{8}$$

where $T_{r,i}$ and $T_{t,i}$ are retrieval value and true value, respectively, and M is the number of data. As for the first model and the fourth model, the values of RMSE are 0.35 °C and 0.45 °C, showing that retrieval results have little deviations, which indicates the high retrieval accuracy. Nevertheless, deviations larger than a few degrees can also be found (the third model), compared with the two models mentioned above. It is because the third smartphone is put into the pocket of the clothing, leading to be less sensitive to the variation of the air temperature. However, the good effect of the fourth model suggests that it is feasible to take advantage of the average battery temperature of different smartphones to smooth deviations and outliers.

Daily mean, minimum, and maximum air temperature are often adopted for evaluating air temperature. These parameters are useful for the research on climate change and modeling of air temperature [25]. Fig. 6 shows results of three parameters by four models. It can be seen that retrieval values of the parameters still positively correlates with true air temperature. For further analysis, values of RMSE of three parameters by four models are calculated in Fig. 7. It shows that values

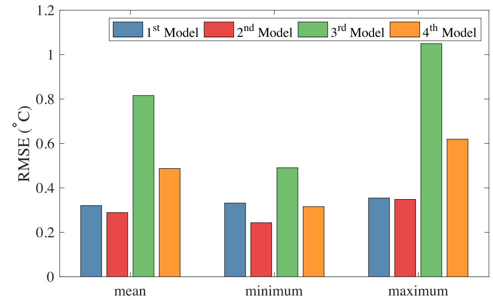

Fig. 7. RMSE of daily mean, minimum, and maximum air temperature by four models.

TABLE I
EVALUATION OF RETRIEVAL AIR TEMPERATURE WITH DIFFERENT NS

	N	ρ^2	*RMSE* (°C)	*MB* (°C)
1st model	60	0.99	0.33	-0.26
	900	0.99	0.33	-0.26
	3600	0.99	0.32	-0.25
2nd model	60	0.99	0.62	-0.55
	900	0.99	0.61	-0.54
	3600	0.99	0.61	-0.54
3rd model	60	0.97	1.27	-1.08
	900	0.97	1.27	-1.08
	3600	0.97	1.24	-1.06
4th model	60	0.99	0.46	-0.37
	900	0.99	0.46	-0.37
	3600	0.99	0.46	-0.37

of RMSE for three parameters are less than 0.8 °C except the third model, and the ones for the first and second model are less than 0.4 °C, which indicates that the method can estimate the air temperature for both high and low values. Compared with retrieval results of the third model, the ones by the fourth model have a higher accuracy, showing that it still works by calculating the average battery temperature of different smartphones.

IV. Discussion

A. Time Interval of N

In Section III, the value of N of (4) is selected to be 60 (1 min) for a robust estimation of the retrieval air temperature. In this section, we discuss whether or not the value of N influences the retrieval air temperature. Table I gives the results of ρ^2, RMSE, and *MB* between the retrieval air temperature and the true air temperature when $N = 60, 900, 1800$, and 3600 (1 min, 15 min, 30 min, and 1 h) for four models. In general, the retrieval results would be more robust as the N is getting larger. However, in this study, values of ρ^2, RMSE, and MB between the retrieval air temperature and the true air temperature barely change with different Ns, showing that the values of N have little influence on the retrieval results when N is larger than 60. The analysis above indicates that it is optimized that set $N = 60$. The value ($N = 60$) provides a short timescale (minute) estimation of the air temperature.

B. Potential of Crowdsourcing Way to Estimate the Air Temperature Using the Smartphone

Crowdsourcing way, the involvement of volunteers in research presented in [16], is widely used, benefiting from the

Internet and the big data. It has invited the public to take part in the scientific research and data collection. The smartphone is a good choice to connect the public and the data measured by its sensors via the Internet. In this study, a preliminary test has been conducted to prove that a smartphone battery temperature sensor can be converted the air temperature by a model, although there are still some errors. However, if the more sensor data of the battery temperature can be obtained through the Internet, then the less errors will be converted in the average of time and space methods [20]. By installing the application and collaborating with communication operators, a huge number of data can be obtained in the future. Thus, we can get a refined, high-temporospatial temperature data for the weather forecast, the research for the heat island effect and the public health.

C. Possible Sources of Error

There are possible sources of error for estimating the air temperature by the smartphone. The central processing unit (CPU) load of the phone may result in increased device temperature, which would overestimate the air temperature. In addition, other factors, such as smartphone model, operating system version, and screen size, also have an impact on the temperature of the phone, which may influence on battery response to air temperature. To solve this error, it is necessary to calculate an estimation model for each smartphone based on the existing data, separately. Further research on the impact needs to be done in the future.

The smartphone, that is not get properly exposed to the environment, may lead to estimation errors. In this study, the most of correlation coefficients of the third phone (unexposed to the environment) in Fig. 2(b) are higher than 0.8, indicating that this phone can still sense the air temperature. However, compared with the other two phones (exposed to the environment), the estimation result of the third phone is less accurate, indicating that the positions of the smartphones can influence the accuracy. To overcome this problem, we present an average estimation model (the 4th model). The result shows that this model can improve the accuracy of the third phone. Other positions of the smartphones, such as the hand of the users, also need to be studied in the future.

V. Conclusion

High temporal–spatial measurement of the air temperature is important for human health and research on the meteorology. However, conventional methods can hardly meet the demands. It is essential to develop a method to solve the problem. As a result, we present a method of estimating the air temperature by the battery temperature sensor of the smartphone with the 1-min sample time in this study. If we collect the battery temperature of widespread smartphones in a crowdsourcing way in the future, the method can provide refined air temperature with high temporal and spatial resolution.

First, a heat transfer retrieval model between the air temperature, smartphone battery temperature, and the temperature of the pocket of the clothing or the desk is established. The model is supposed to be a linear model. Then, coefficients of the retrieval model are obtained by the data set measured by the smartphone battery sensor and the thermometer datalogger in the linear fitting method. Finally, we retrieve the air temperature in a specific site with a time resolution of 1 min based on the retrieval model by three independent smartphones.

The retrieval temperature of four models strongly, positively correlates to the true air temperature measured by the thermometer datalogger, which indicates that the retrieval air temperature model can sense the variation of the air temperature. Meanwhile, RMSEs of the first and fourth model are 0.35 °C and 0.45 °C and MAEs of two models are 0.28 °C and 0.36 °C, implying that the two modes have the high retrieval accuracy. Deviations of the third model are larger than the others because the third smartphone is put into the pocket of the clothing, which leads to be less sensitive to the variation of the air temperature. However, this problem can be solved by taking the average of battery temperature of three smartphones. The method provides a feasible way to smooth deviations and outliers. Additionally, values of N in (4) have been discussed and results of Table I show that whatever N is equal to 60, 900, 1800, or 3600, the retrieval air temperature change little as for ρ^2, RMSE, MB, and MAE. It suggests that the retrieval model can provide a short timescale (minute) and robust estimation of the air temperature by smartphone temperature sensors. In order to improve the estimation accuracy of air temperature, further research on possible sources of error needs to be done in the future.

This article may provide a novel way to estimate the air temperature in a small scale and specific site with a time resolution of 1 min based on the heat transfer model by smartphones, which is more feasible in reality. The crowdsourcing method for measuring the air temperature by smartphones is promising, as smartphones are widely spread in the world, especially in urban areas, which can provide the high temporal–spatial measurements. The smartphone may become a more refined measurement of the air temperature in a crowdsourcing way in the future.

Acknowledgment

The authors thank anonymous reviewers for providing helpful advice.

References

[1] X. R. Zhao, Z. Sheng, J. W. Li, H. Yu, and K. J. Wei, "Determination of the 'wave turbopause' using a numerical differentiation method," *J. Geophys. Res. Atmosp.*, vol. 124, no. 20, pp. 10592–10607, 2019.

[2] L. T. Alain *et al.*, "Impact of the 2003 heatwave on all-cause mortality in 9 French cities," *Epidemiology*, vol. 17, pp. 75–79, Jan. 2006.

[3] L. Filleul *et al.*, "The relation between temperature, ozone, and mortality in nine French cities during the heat wave of 2003," *Environ. Health Perspect.*, vol. 114, no. 9, pp. 1344–1347, 2006.

[4] M. Laaidi, K. Laaidi, and J.-P. Besancenot, "Temperature-related mortality in France, a comparison between regions with different climates from the perspective of global warming," *Int. J. Biometeorol.*, vol. 51, pp. 145–153, Nov. 2006.

[5] G. J. Steeneveld, S. Koopmans, B. G. Heusinkveld, L. W. A. Van Hove, and A. A. M. Holtslag, "Quantifying urban heat island effects and human comfort for cities of variable size and urban morphology in the Netherlands," *J. Geophys. Res. Atmosp.*, vol. 116, no. D20, p. 14, 2011.

[6] B. G. Heusinkveld, G. J. Steeneveld, L. W. A. Hove, C. M. J. Jacobs, and A. A. M. Holtslag, "Spatial variability of the Rotterdam urban heat island as influenced by urban land use," *J. Geophys. Res. Atmosp.*, vol. 119, no. 2, pp. 677–692, 2014.
[7] C. L. Muller *et al.*, "Crowdsourcing for climate and atmospheric sciences: Current status and future potential," *Int. J. Climatol.*, vol. 35, no. 11, pp. 3185–3203, 2015.
[8] D. G. Miralles, A. J. Teuling, C. C. V. Heerwaarden, and J. V.-G. D. Arellano, "Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation," *Nat. Geosci.*, vol. 7, no. 5, pp. 345–349, 2014.
[9] S. Kotthaus, H. C. Ward, C. S. B. Grimmond, and J. G. Evans, "Flux measurements in Southern England by KCL and CEH," *Flux Lett.*, vol. 5, no. 1, pp. 25–31, 2012.
[10] C. L. Muller, L. Chapman, C. S. B. Grimmond, D. T. Young, and X. Cai, "Sensors and the city: A review of urban meteorological networks," *Int. J. Climatol.*, vol. 33, no. 7, pp. 1585–1600, 2013.
[11] D. Wolters and T. Brandsma, "Estimating the urban heat island in residential areas in The Netherlands using observations by weather amateurs," *J. Appl. Meteorol. Climatol.*, vol. 51, no. 4, pp. 711–721, 2012.
[12] S. Bell, C. Dan, and L. Bastin, "The state of automated amateur weather stations," *Weather*, vol. 68, no. 2, pp. 36–41, 2013.
[13] N. Castell *et al.*, "Mobile technologies and services for environmental monitoring: The citi-sense-MOB approach," *Urban Climate*, vol. 14, pp. 370–382, Dec. 2015.
[14] L. Chapman, C. Bell, and S. Bell, "Can the crowdsourcing data paradigm take atmospheric science to a new level? A case study of the urban heat island of London quantified using Netatmo weather stations," *Int. J. Climatol.*, vol. 37, no. 9, pp. 3597–3605, 2017.
[15] F. Meier, D. Fenner, T. Grassmann, M. Otto, and D. Scherer, "Crowdsourcing air temperature from citizen weather stations for urban climate research," *Urban Climate*, vol. 19, pp. 170–191, Jan. 2017.
[16] J. L. Dickinson, B. Zuckerberg, and D. N. Bonter, "Citizen science as an ecological research tool: Challenges and benefits," *Annu. Rev. Ecol. Syst.*, vol. 41, no. 41, pp. 149–172, 2010.
[17] K. Song, X. Liu, T. Gao, M. Yin, and B. He, "The feasibility analysis of cellphone signal to detect the rain: Experimental study," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 7, pp. 1158–1162, Jul. 2020.
[18] M. Bhattacharjee, F. Nikbakhtnasrabadi, and R. Dahiya, "Printed chipless antenna as flexible temperature sensor," *IEEE Internet Things J.*, early access, Jan. 13, 2021, doi: 10.1109/JIOT.2021.3051467.
[19] P. Escobedo, M. Bhattacharjee, F. Nikbakhtnasrabadi, and R. Dahiya, "Smart bandage with wireless strain and temperature sensors and battery-less NFC tag," *IEEE Internet Things J.*, early access, Dec. 30, 2021, doi: 10.1109/JIOT.2020.3048282.
[20] A. Overeem, J. C. R. Robinson, H. Leijnse, G. J. Steeneveld, B. K. P. Horn, and R. Uijlenhoet, "Crowdsourcing urban air temperatures from smartphone battery temperatures," *Geophys. Res. Lett.*, vol. 40, pp. 4081–4085, Aug. 2013.
[21] A. M. Droste *et al.*, "Crowdsourcing urban air temperatures through smartphone battery temperatures in São Paulo, Brazil," *J. Atmosp. Ocean. Technol.*, vol. 34, pp. 1853–1866, Sep. 2017.
[22] H. Ali, H. A. Khan, and M. G. Pecht, "Evaluation of Li-based battery current, voltage, and temperature profiles for in-service mobile phones," *IEEE Access*, vol. 8, pp. 73665–73676, 2020, doi: 10.1109/ACCESS.2020.2988728.
[23] I. Pincovschi and D. S. Stefan, "Effect of temperature and sulfur dioxide pressure on natural water pollution," *Revista De Chimie*, vol. 64, no. 9, pp. 1021–1023, Sep. 2013.
[24] S. Heddam, M. Ptak, and S. Zhu, "Modelling of daily lake surface water temperature from air temperature: Extremely randomized trees (ERT) versus Air2Water, MARS, M5Tree, RF and MLPNN," *J. Hydrol.*, vol. 588, Sep. 2020, Art. no. 125130.
[25] J. Bilbao, A. H. D. Miguel, and H. D. Kambezidis, "Air temperature model evaluation in the north mediterranean belt area," *J. Appl. Meteorol.*, vol. 41, pp. 872–884, Aug. 2002.

Kun Song was born in China in 1991. He received the B.S. and M.S. degrees in atmospheric measurement techniques from PLA University of Science and Technology, Nanjing, China, in 2014 and 2017, respectively. He is currently pursuing the Ph.D. degree in atmospheric science with the National University of Defense Technology, Changsha, China.

His research interests include atmospheric science, atmospheric measurement, and remote sensing techniques and instruments.

Xichuan Liu received the master's and Ph.D. degrees in atmospheric measurement techniques from PLA University of Science and Technology, Nanjing, China, in 2010 and 2014, respectively.

He is currently a Lecturer with the College of Meteorology and Oceanography, National University of Defense Technology, Changsha, China. His research interests include atmospheric physics, atmospheric measurement, and remote sensing techniques and instruments.

Taichang Gao received the B.S. degree in dynamic meteorology from the Air Force College of Meteorology, Nanjing, China, in 1982.

He is currently a Professor with the College of Meteorology and Oceanography, National University of Defense Technology, Changsha, China. His research interests include atmospheric measurement and remote sensing techniques and instruments.